Enhance Operation with AI: Reimagining Energy Infrastructure as Personalized Software Assets

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Why AI in HVAC?

- Most standard U.S. HVAC systems cannot directly adjust **fan speed** and **supply air temperature (SAT)**
- Fan power is a major energy load: studies show that fan speed plays a large role in energy consumption [1]
- Because of the **cubic fan law**, reducing fan speed along with adjusting SAT can achieve the same target temperature with much lower energy consumption than conventional constant-speed approaches.
- Yet only **~4% of commercial** and **~5% of residential** HVAC systems use load control technology [2, 3]
- Newer trends show **>60% of new commercial HVAC units now use Variable Frequency Drives (VFDs)** for fan control [4]
- Recent work combines **transfer learning and TinyML** to deploy cloud-trained models on microcontrollers for **personalized control at the edge** [5]
- We adopt this **hybrid cloud–edge approach (HM)** for HVAC fan/SAT prediction and personalization using both historical and real time data
- Our method predicts the minimum fan speed and SAT required to reach the target temperature, **reducing energy use while maintaining comfort**. This approach can benefit a wide range of facilities: from large commercial and recreational buildings to hospitals and residential units.

In this research, we focus specifically on the air-conditioning (AC) aspect of HVAC.

Current Approach	Our Approach
Thermostat with simple deadband control . Turns on when above the upper deadband limit, off when below the lower limit • an speed fixed to 0% or 100% (all-or-nothing operation) • Evaporator temperature held constant	**Hybrid model (Cloud ML + Local Personalization)** • Predicts fan speed and supply air temperature (SAT) dynamically, using features such as outdoor temperature, current room temperature, room size, and setpoint • Fan speed adjustable from 0% to 100% • Evaporator/SAT variable rather than fixed, adapting to load
Pros: • No learning or data required • Very simple and easy to maintain • Stable room temperature Cons: • All-or-nothing fan control wastes energy (cubic fan law → high power penalty) • Constant low evaporator temperature can lead to **overcooling**, even when only 1–2 °C of cooling is needed • No adaptability to external conditions (e.g., outdoor temp, building load, occupancy)	Pros: • Lower energy use via optimized fan speed and SAT • Maintains steady room temperature with personalization that learns site-specific patterns (e.g., room size, insulation, occupancy) Cons: • Requires cloud-based training and periodic updates • More potential points of failure → requires monitoring and maintenance • Higher upfront cost and system complexity compared to simple thermostats, but offset by lower energy consumption

Methodology

Figure 1 illustrates the workflow, where cloud ML and edge devices (individual HVAC units) interact. In this study, the **desktop acts as the cloud**, and the **ESP32 microcontroller** serves as the edge device for proof of concept.

Cloud (Desktop):
- Trained with **Gradient Boosting Regressor**.
- **Features**: outdoor, room, and target temps, and room size
- **Targets**: fan speed (0.0-1.0) and SAT (8-16°C).
- A **TinyML** model is distilled from DM for deployment.

Edge (Device):
- Receives the TinyML model from the cloud and applies **local personalization** = Hybrid Model.
- Affine correction layer $y^* = W \cdot y + b$
- **Online updates using feedback** from room state
- Enables **real-time adaptation** to environment and system variance

Test Setup:
- 4 day long scenario with changing outdoor temperature and sudden temperature spikes and drops
- Predictions compared across three models:
  - **Thermostat Model (TM):** simple deadband control.
  - **Desktop Model (DM):** cloud-trained model without personalization
  - **Hybrid Model (HM):** DM + personalization

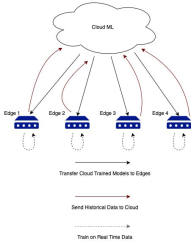

Fig 1. Hybrid Model Diagram

Results & Discussion:

Figures 2 and 3 compare the performance of three models for 4 day scenario with changing outdoor temperature.
- **Thermostat Model (TM)**: Baseline conventional deadband control. The AC turns on when room temperature > setpoint + deadband/2, and off when room temperature < setpoint – deadband/2. This was simulated on desktop (Mac Mini).
- **Desktop Model (DM)**: Cloud-trained model, evaluated and simulated on desktop.
- **Hybrid Model (HM)**: DM combined with local personalization on the edge device (ESP32 microcontroller).

Figure 4 shows, for each model, the predicted room temperature, supply air temperature (SAT), and fan speed.

TM:
- As shown in Fig. 3, TM has the highest mean absolute error (MAE) among the three models. This is expected given the simplicity of the deadband control.
- TM also shows the highest overall energy consumption (Fig. 3), mainly due to its "**all-or-nothing**" fan operation. This appears as grey fan-speed spikes in Fig. 4 Panel C.
- **Overcooling** is observed in Fig. 4: despite a 1 °C deadband (stop cooling at 22.5 °C), the room temperature drops below 22 °C.

DM:
- DM produces accurate fan speed and SAT predictions, maintaining room temperature closer to the setpoint compared to TM (Fig. 2).
- Energy consumption is reduced compared to TM (Fig. 3).
- Fig. 4 Panels A and B show DM's "**micro-control**" – small fan speed spikes and a steady SAT that bring the room back to setpoint even with only a 0.1–0.2 °C deviation.

HM:
- HM shows the most accurate predictions to maintain the room temperature very close to the target temperature across all 4 days.
- HM achieves the lowest total energy consumption (Fig. 3). This is due to its **smoother, lower fan speed** (Fig. 4) compared to the frequent spikes seen in TM and DM, while still effectively reaching the setpoint by adjusting SAT.
- However, predictions tend to be less accurate at lower outdoor temperatures, though the error remains within 0.15 °C.

Conclusion

Both DM and HM produce more stable room temperatures than the conventional TM. Fig. 4 Panel C shows that DM and HM learn to shut off the fan completely when outdoor temperature is at its lowest. However, HM outperforms DM in total energy consumption, and its **online learning from room temperature feedback** allows it to continuously correct errors. HM's predictions resulted in the smoothest room temperature, which gives extra comfortability. This technology will be especially beneficial for innovative systems like HYDECO, a solar-powered HVAC that allows configuration of multiple internal parameters.

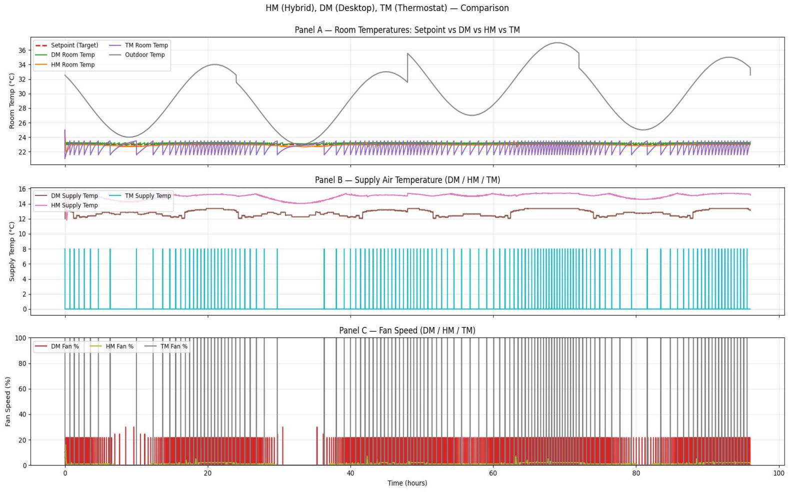

Fig 4. Room Temp, Fan Speed, SAT Comparison by Models

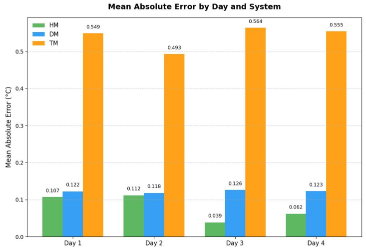

Fig 2. Mean Abs, Error Comparison for Each Day

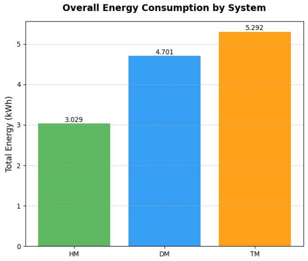

Fig 3. Overall Energy Consumption by Models

Limitations & Future Work:

Training Data:
- The dataset used an unrealistic constraint (fixed 25 °C starting temperature), which limits DM's ability to generalize.
- Real HVAC systems require additional features such as humidity, occupancy, building dynamics, furnishing factors, and air leakage, all of which interact with the thermal capacitance of the space.
- In this study, DM was trained on outdoor temperature and room size variation, but broader, more diverse training sets are needed.

Simulation Scope:
- Although the simulation reflects sudden outdoor temperature spikes and drops, the HM requires validation across a wider spectrum of conditions.
- Room temperature and power simulations were simplified and need to be refined for realism
- Models were trained and tested exclusively on simulated data; validation with real-world HVAC data is essential.

System Deployment:
- A robust cloud pipeline is required to distribute updated DM models to edge devices at scale.

Next steps:
- Validate performance across diverse building types and operating scenarios.
- Integrate **HYDECO** metrics for comprehensive evaluation of both energy efficiency and occupant comfort.

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